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LOCAL ASYMPTOTIC NORMALITY FOR PROGRESSIVELY CENSORED LIKELIHOOD--ETC(L  
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N00014-79-C-0522

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LOCAL ASYMPTOTIC NORMALITY FOR PROGRESSIVELY CENSORED  
LIKELIHOOD RATIO STATISTICS AND APPLICATIONS

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Summary. Let  $X_{n,1} \leq X_{n,2} \leq \dots \leq X_{n,n}$  be the ordered variables corresponding to a random sample of size  $n$  with respect to a family of probability measures  $\{P_\theta: \theta \in \Theta\}$  where  $\Theta$  is an open subset of the real line. In many practical situations the  $X_{n,i}$  are the observables and experimentation must be curtailed prior to  $X_{n,n}$ . If  $\tau_n$  is a stopping variable adapted to the  $\sigma$ -fields  $\{\sigma(X_{n,1}, \dots, X_{n,k}) : 1 \leq k \leq n\}$  and  $P_{n,\theta}$  the projection of  $P_\theta$  onto  $\sigma(X_{n,1}, \dots, X_{n,\tau_n})$ , the local asymptotic normality of the stopped progressively censored likelihood ratio statistics  $\Lambda_{n,\tau_n} = dP_{n,\theta} / dP_{n,\theta_0}$  is established with  $\theta_n = \theta + u n^{-1/2} \in \Theta$  and  $\theta, u$  held fixed, under certain conditions on the underlying distribution and on  $\tau_n$ . Conditions are also given to ensure the local asymptotic normality of likelihood ratio statistics where the underlying observations are given in a series scheme.

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AMS Classifications: 60B10, 62F10

Key Words and Phrases: Clinical trials, life-testing, likelihood ratio statistics, progressive censoring, stopping variables.

\* Research sponsored in part by the Office of Naval Research under ONR Contract N00014-79-C-0522 and by the Biomedical Research Support Grant Program of the ~~National Institutes~~ of Health under BRSG Grant S07-RR07049-14.

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# 1. Introduction.

There have been in recent times <sup>were made</sup> ~~several~~ investigations of the notion of local asymptotic normality (LAN) of a family of probability distributions. The usefulness of this concept in problems of the theory of asymptotic estimation and hypothesis testing <sup>was</sup> ~~has been~~ demonstrated, in the papers of LeCam and in LeCam (1960) <sup>can be found</sup> ~~can be found~~ a comprehensive examination of sets of conditions ensuring the LAN for different families of probability distributions. Much attention has been focused on distributions connected with sequences of independent and identically distributed (iid) observations or those associated with a homogeneous Markov chain. See, for example Hájek (1972), Roussas (1972), Ibragimov and Khas'minskii (1972), Inagaki and Ogata (1975). The case of independent but non-identically distributed observations is also discussed in Phillipou and Roussas (1973) and Ibragimov and Khas'minskii (1975).

→ In this paper ~~we shall present~~ <sup>are presented</sup> conditions ensuring the LAN for distributions connected with certain observations, which are neither independent nor identically distributed, when a class of stopping variables is incorporated in a natural way into the basic framework. The primary motivation for our study is the following situation which arises naturally in the context of clinical trials and life tests. The typical feature encountered here is that even though the survival times of  $n \geq 1$  specimens under a life test may be iid random variables (rv)  $X_1, \dots, X_n$ , with respect to a family of probability measures  $\{P_\theta : \theta \in \Theta\}$  the actual observables are the dependent ordered variables  $X_{n,1}, \dots, X_{n,n}$  of the responses of the sample. Limitations on time and cost and ethical reasons invariably force termination of experimentation before the last observable  $X_{n,n}$  is recorded and thus, in practice, sampling may be terminated after a pre-specified duration of time (truncation)



or once a pre-specified proportion of units have responded (censoring). Alternatively, in progressive censoring, the experiment is monitored from the onset with the data continually updated so that at any stage if the current accumulated evidence suggests a clear statistical decision, then experimentation can be curtailed with a concomitant reduction in cost and sacrifice of lives of experimental units. Thus we are led naturally to the incorporation of a class of stopping variables  $\tau_n$  into our basic framework, where for each  $n \geq 1$ ,  $\tau_n$  is defined in terms of the recorded observables among  $X_{n,1}, \dots, X_{n,n}$ . If  $P_{n,\theta}$  denotes the restriction of  $P_\theta$  to the  $\sigma$ -field generated by  $X_{n,1}, \dots, X_{n,\tau_n}$ , the asymptotic behavior of the likelihood ratios  $dP_{n,\theta_n} / dP_{n,\theta}$  for certain sequences of parameter values  $\theta_n$  will be of interest. It is to this question that this paper is devoted. Note that when  $\tau_n$  is degenerate at  $n$ , for all  $n$ ,  $dP_{n,\theta_n} / dP_{n,\theta}$  reduce to the likelihood ratio for the  $n$  iidrv  $X_1, \dots, X_n$  and the limiting distribution of these ratios has been studied with  $\theta_n = \theta + un^{-1/2}$ . An investigation of the general situation was initiated by Sen (1976) for certain likelihood ratio processes. Here  $\tau_n$  is assumed degenerate at  $r_n$  and  $r_n/n$  tends to  $\alpha \in (0,1]$  as  $n \rightarrow \infty$ . By considering random  $\tau_n$  we allow for wider applicability and the results that we obtain are stronger and assume fewer regularity conditions.

The basic notation and assumptions are summarized in Section 2. In Section 3, the main theorems in this paper are stated and their proofs taken up in Section 4 after some auxiliary lemmata are established. In the last section we make a few comments on our assumptions and discuss an extension of our results to likelihood ratio statistics when the observations follow a series scheme.

## 2. Preliminary notions and the main theorems.

Let  $\{X_i : i \geq 1\}$  be a sequence of iidrv's whose probability distribution  $\nu_\theta$  on the Borel line  $(R, \mathcal{B})$  depends on a parameter  $\theta$  belonging to an open subset  $\Theta$  of  $R$ . We suppose that the family of measures  $\{\nu_\theta : \theta \in \Theta\}$  is dominated by Lebesgue measure  $\mu$  on  $(R, \mathcal{B})$  and write  $f_\theta(\cdot) = d\nu_\theta/d\mu$  for a version of the probability density function (pdf) and  $F_\theta(\cdot)$  for the corresponding distribution function (df). Let  $(R_j, \mathcal{B}_j)$ ,  $j \geq 1$  be copies of the Borel line and set  $(X^*, A^*) = \prod_{j=1}^\infty (R_j, \mathcal{B}_j)$  with  $P_\theta$  denoting the product measure of the  $\nu_\theta$  induced on  $A^*$ .  $E_\theta$  will denote the expectation evaluated with respect to  $P_\theta$ .

We envisage a clinical trial or life test experiment in which the  $X_i$  denote survival or response times and consequently they are nonnegative and the observable variables for a sample of  $n \geq 1$  specimens are the order statistics  $X_{n,1} < \dots < X_{n,n}$  corresponding to  $X_1, \dots, X_n$ . By the continuity of  $F_\theta$  ties among the observables may be disregarded with probability one.

For simplicity in script we denote by

$$Z_k = X_{n,k}, \quad \underline{Z}^{(k)} = (Z_1, \dots, Z_k), \quad 1 \leq k \leq n; \quad Z_0 = \underline{Z}^{(0)} = 0. \quad (2.1)$$

The  $\sigma$ -field generated by  $\underline{Z}^{(k)}$  is written  $\mathcal{B}_{n,k}$  and  $\mathcal{B}_{n,0}$  is the trivial  $\sigma$ -field. For each  $n \geq 1$ , let  $\tau_n$  be a stopping variable adapted to  $\{\mathcal{B}_{n,k} : 1 \leq k \leq n\}$ . We denote by  $P_{n,\theta}$  the projection of  $P_\theta$  on  $\mathcal{B}_{n,\tau_n} = \sigma(\underline{Z}^{(\tau_n)})$ . The family of probability measures  $\{P_{n,\theta} : \theta \in \Theta\}$  is said to be locally asymptotically normal (LAN) at  $\theta_0 \in \Theta$  if for some positive nonstochastic sequence  $\{\varphi_n : n \geq 1\}$  we have for each  $u \in R$

$$\frac{dP_{n,\theta_0+u\varphi_n^{-1}}}{dP_{n,\theta_0}} = \exp\{u W_n(\theta_0) - \frac{1}{2} u^2 + \delta_n(u, \theta_0)\} \quad (2.2)$$

where  $\{W_n(\theta_0) : n \geq 1\}$  converges weakly under  $P_{\theta_0}$  to a Gaussian  $(0,1)$  variable and, for each  $u$ ,  $\{\delta_n(u, \theta_0) : n \geq 1\}$  converges in  $P_{\theta_0}$ -probability to zero.

Now for each  $k$ ,  $1 \leq k \leq n$  let  $P_{n,\theta}^{(k)}$  denote the projection of  $P_\theta$  onto  $B_{n,k}$ . Then with respect to Lebesgue measure  $\mu_k$  in  $R^k$  the joint pdf of  $Z^{(k)}$  is given by

$$p_\theta(Z^{(k)}, n) = \{n!/(n-k)!\} \left\{ \prod_{i=1}^k f_\theta(z_i) \right\} \{1-F_\theta(z_k)\}^{n-k} \quad (2.3)$$

defined on  $A_{n,k} = \{Z^{(k)} : 0 < z_1 < \dots < z_k < \infty\}$ , and the conditional pdf of  $Z_k$  given  $B_{n,k-1}$  is

$$q_\theta(z_k | B_{n,k-1}) = (n-k+1) f_\theta(z_k) \{1-F_\theta(z_k)\}^{n-k} / \{1-F_\theta(z_{k-1})\}^{n-k+1} \quad (2.4)$$

defined for  $z_k > z_{k-1}$ . Let  $\theta_0$  be a fixed but otherwise arbitrary element of  $\Theta$  and consider the sequence  $\{\theta_n\}$  where

$$\theta_n = \theta_0 + u n^{-1/2}, \quad u \in R. \quad (2.5)$$

For  $\theta_n \in \Theta$  and for each  $k$ ,  $1 \leq k \leq n$ , we define the progressively censored likelihood ratio statistics (PCLRS) by

$$\frac{dP_{n,\theta_n}^{(k)}}{dP_{n,\theta_0}^{(k)}} = \Lambda_{n,k}(u) = p_{\theta_n}(Z^{(k)}, n) / p_{\theta_0}(Z^{(k)}, n). \quad (2.6)$$

Then  $dP_{n,\theta_n} / dP_{n,\theta_0} = \Lambda_{n,\tau_n}$  and we are interested in the asymptotic behavior of  $\Lambda_{n,\tau_n}$ . In order to state our assumptions we need the hazard rate

$$r_\theta(x) = f_\theta(x) / \{1-F_\theta(x)\} \quad (2.7)$$

and survival function

$$G_\theta(x) = 1-F_\theta(x). \quad (2.8)$$

For any  $\mathcal{B}$ -measurable nonnegative function  $h_\theta(x)$ , let  $\dot{h}_\theta(x) = \frac{\partial}{\partial \theta} (\log h_\theta(x))$ .

We now state the assumptions under which we derive the LAN of

$\{P_{n,\theta} : \theta \in \Theta\}$  at  $\theta_0$ .

(A1) For all  $\theta$  in some neighborhood  $N_{\theta_0}$  of  $\theta_0 \in \Theta$ ,  $f_\theta(x) > 0$  for all  $x \in \mathbb{R}^+ = [0, \infty)$  and there exists a  $\mu$ -integrable function  $U$  such that for  $\mu$ -almost all  $x \in \mathbb{R}^+$ ,  $\theta \rightarrow f_\theta(x)$  is continuously differentiable and  $|\frac{\partial f_\theta}{\partial \theta}| \leq U$ , for all  $\theta \in N_{\theta_0}$  and almost all  $x \in \mathbb{R}^+$ .

(A2) For  $\mu$ -almost all  $x \in \mathbb{R}^+$ ,  $x \rightarrow \dot{f}_{\theta_0}(x)$  is differentiable.

(A3) There exists a number  $\delta > 0$  such that  $E_{\theta_0} |\dot{f}_{\theta_0}(X)|^{2+\delta} < \infty$  and  $E_{\theta_0} |\ddot{f}_{\theta_0}(X)|^{2+\delta} < \infty$ .

(A4) There exists a constant  $\alpha \in (0, 1]$  such that  $n^{-1}\tau_n \rightarrow \alpha$  in  $P_{\theta_0}$ -

probability. Suppose  $J_\alpha = J_\alpha(\theta_0) = \int_0^{F_{\theta_0}^{-1}(\alpha)} \dot{f}_{\theta_0}^2(x) dF_{\theta_0}(x) > 0$ .

(A5) For each  $k$ ,  $1 \leq k \leq n$ ,  $\theta \rightarrow \int_{z_{k-1}}^\infty q(z | \mathcal{B}_{n,k-1}) d\mu(z)$  is differentiable through the integral sign at  $\theta_0$ .

(A6) For each  $u \in \mathbb{R}$

$$\lim_{n \rightarrow \infty} E_{\theta_0} \left\{ \sup_{|\theta - \theta_0| \leq |u|n^{-1/2}} n^{-1} \sum_{i=1}^n \int_{z_{i-1}}^\infty d\mu \left[ \frac{\partial}{\partial \theta} \{q_\theta(z | \mathcal{B}_{n,i-1})\}^{\frac{1}{2}} - \frac{\partial}{\partial \theta_0} \{q_{\theta_0}(z | \mathcal{B}_{n,i-1})\}^{\frac{1}{2}} \right]^2 \right\} = 0,$$

$$\text{where } \frac{\partial}{\partial \theta_0} \{q_{\theta_0}(z | \mathcal{B}_{n,i-1})\}^{\frac{1}{2}} = \left( \frac{\partial}{\partial \theta} \{q_\theta(z | \mathcal{B}_{n,i-1})\}^{\frac{1}{2}} \right)_{\theta=\theta_0}.$$

Assumption (A2) provides for a Lyapunov Condition for the derivatives

$\{\dot{q}_\theta(z_k | \mathcal{B}_{n,k-1}), 1 \leq k \leq n\}$  which form a martingale in view of (A5).

Assumption (A6), given in terms of the square root of the conditional pdf is a weak continuity condition. Our restriction on the growth of  $\tau_n$  is



(A4).  $J_\alpha$  is the analog of the Fisherian Information for our framework. Indeed for  $\alpha = 1$  this reduces to  $J_1 = E_{\theta_0} (\dot{f}_{\theta_0}(X))^2$  which is the Fisher Information of an unit sample from the distribution  $F_{\theta_0}$ .

For each  $k$ ,  $1 \leq k \leq n$  denote by

$$\xi_{n,k} \equiv \xi_{n,k}(Z^{(k)}, \theta_0) = \dot{p}_{\theta_0}(Z^{(k)}, n) \quad (2.9)$$

and let

$$J_{n,k} = E_{\theta_0} \{\xi_{n,k}^2\}. \quad (2.10)$$

With a slight abuse of standard notation we set

$$J_{n,\tau_n} = E_{\theta_0} \{\xi_{n,\tau_n}^2\}. \quad (2.11)$$

Now if

$$\xi_{n,k}^* \equiv \xi_{n,k}^*(Z^{(k)}, \theta_0) = \dot{q}_{\theta_0}(Z_k | \mathcal{B}_{n,k-1}), \quad 1 \leq k \leq n \quad (2.12)$$

and  $\sigma_{n,k}^{*2} = E_{\theta_0}(\xi_{n,k}^{*2} | \mathcal{B}_{n,k-1})$  let

$$V_{n,k} = \sum_{i=1}^k \sigma_{n,i}^{*2}. \quad (2.13)$$

Define the sequence of statistics  $\{W_{n,\tau_n} : n \geq 1\}$  by

$$W_{n,\tau_n} = \xi_{n,\tau_n} / J_{n,\tau_n}^{1/2}. \quad (2.14)$$

### 3. Main Theorems.

Define processes  $u \rightarrow \Lambda^\pm(u)$ ,  $u \in \mathbb{R}$  by

$$\Lambda^\pm(u) = \exp\{u J_\alpha^{1/2} \zeta \pm \frac{1}{2} u^2 J_\alpha\} \quad (3.1)$$

where  $\zeta$  is a standard normal variable. Then we have

Theorem 3.1. Under assumptions A1-A6 for each  $u \in \mathbb{R}$  the following representation holds.



$$\Lambda_{n, \tau_n}(u) = \exp\{u J_{\alpha}^{\frac{1}{2}} W_{n, \tau_n} - \frac{1}{2} u^2 J_{\alpha} + \delta_n\} \quad (3.2)$$

where  $L(W_{n, \tau_n} | P_{\theta_0}) \rightarrow N(0, 1)$  and for each  $u \in R$ ,  $\delta_n(u) \rightarrow 0$  in  $P_{\theta_0}$ -probability.

Therefore we may say the family of probability measures  $\{P_{n, \theta} : \theta \in \Theta\}$  is LAN at  $\theta_0 \in \Theta$ . For statistical applications it is necessary to investigate the behavior of  $\Lambda_{n, \tau_n}$  under both  $P_{\theta}$  and  $P_{\theta_n}$ .

Theorem 3.2. Under assumptions A1-A6 for each  $u \in R$

$$L(\Lambda_{n, \tau_n}(u) | P_{\theta_0}) \rightarrow L(\Lambda^-(u)) \quad (3.3)$$

and

$$L(\Lambda_{n, \tau_n}(u) | P_{\theta_n}) \rightarrow L(\Lambda^+(u)). \quad (3.4)$$

In the framework which we have described the observable variables are the ordered observations  $Z_1, \dots, Z_n$  corresponding to the sample  $X_1, \dots, X_n$  and therefore it is appropriate to formulate statistical procedures in terms of the  $Z_i$  rather than the  $X_i$  themselves. Accordingly we consider a sequence of statistics  $\{T_{n, k} = T_{n, k}(Z^{(k)}), 1 \leq k \leq n\}$  and the stopped sequence  $\{T_{n, \tau_n} : n \geq 1\}$  which then leads to the adoption of the sequential plan  $(T_{n, \tau_n}, \tau_n)$ . We shall not pursue here the interesting question of the optimality (in some sense) of such procedures but, as an application of our previous theorems we establish a result which may be connected with its resolution.

Let  $\mu_k$  denote Lebesgue measure on  $(R^k, B^k)$  and  $E_{n, k} \in B^k$  be the set on which  $\tau_n = k$ . Theorem 3.3 is the Cramér-Rao inequality and Theorem 3.4 gives a lower bound for the asymptotic variance of certain  $T_{n, \tau_n}$ .

Theorem 3.3. Suppose conditions A1-A5 hold for each  $\theta_0 \in \Theta$ . For each  $k$ ,  $1 \leq k \leq n$  suppose  $E_{\theta} T_{n, k}^2 < \infty$  and  $\int_{E_{n, k}} T_{n, k}(z^{(k)}) p_{\theta}(z^{(k)}, n) d\mu_k(z^{(k)})$  be differentiable through the integral sign with respect to  $\theta$ . Then for each

$\theta \in \Theta$

$$\text{Var}_{\theta}(T_{n,\tau_n}) \geq \left(\frac{d}{d\theta} \lambda_n(\theta)\right)^2 / J_{n,\tau_n}(\theta) \quad (3.5)$$

where  $\lambda_n(\theta) = E_{\theta} T_{n,\tau_n}$ . If equality obtains for sufficiently large  $n$  and  $\lim_{n \rightarrow \infty} \frac{d}{d\theta} \lambda_n(\theta) = \lambda_{\alpha}'(\theta)$  exists, then

$$L[n^{1/2}(T_{n,\tau_n} - \lambda_n(\theta)) | P_{\theta}] \rightarrow N(0, \lambda_{\alpha}^2(\theta) / J_{\alpha}(\theta)). \quad (3.6)$$

Theorem 3.4. Suppose conditions A1-A6 hold for each  $\theta_0 \in \Theta$  and there exists functions  $\mu_{\alpha}(\theta)$ ,  $v_{\alpha}^2(\theta)$  with  $v_{\alpha}^2(\theta) > 0$ ,  $\mu_{\alpha}'(\theta) \neq 0$  and continuous on  $\Theta$  such that for each  $\theta \in \Theta$

$$L[n^{1/2}(T_{n,\tau_n} - \mu_{\alpha}(\theta)) | P_{\theta}] \rightarrow N(0, v_{\alpha}^2(\theta)). \quad (3.7)$$

Then

$$v_{\alpha}^2(\theta) \geq (\mu_{\alpha}'(\theta))^2 / J_{\alpha}(\theta), \quad (3.8)$$

for almost all  $\theta \in \Theta$ .

#### 4. Auxiliary lemmata and proofs of the main theorems.

The particular choice of local alternatives  $\theta_n$  of (2.5) originates from the fact that our assumptions ensure  $n^{-1}J_{n,\tau_n} \rightarrow J_{\alpha}$ . To demonstrate this we first establish two auxiliary results.

Let  $\{Y_i; i \geq 1\}$  be a sequence of iidrv's with a strictly increasing continuous df  $H$  having support  $R^+$ . Let  $Y_{n,1}, \dots, Y_{n,n}$  be the ordered observations of the sample  $Y_1, \dots, Y_n$  and  $v_n$  a rv with values in  $\{1, \dots, n\}$ .

Lemma 4.1. Let  $g : R^+ \rightarrow R$  be a measurable function such that  $E|g(Y_1)| < \infty$ .

Suppose  $n^{-1}v_n \rightarrow \alpha \in (0,1]$  in probability. Then

$$n^{-1} \sum_{i=1}^{v_n} g(Y_{n,i}) \xrightarrow{L_1} \int_0^{H^{-1}(\alpha)} g(x) dH(x).$$

Proof. Let  $H_n$  be the empirical df of  $Y_1, \dots, Y_n$ . Then

$$n^{-1} \sum_{i=1}^{v_n} g(Y_{n,i}) = \int_0^{H_n^{-1}(n^{-1}v_n)} g(x) dH_n(x) \quad (4.1)$$

where  $H_n^{-1}(x) = \inf\{t \in \mathbb{R} : H_n(t) \geq x\}$ . Therefore

$$\begin{aligned} n^{-1} \sum_{i=1}^{v_n} g(Y_{n,i}) - \int_0^{H^{-1}(\alpha)} g(x) dH(x) & \quad (4.2) \\ &= \left\{ \int_0^{H_n^{-1}(n^{-1}v_n)} g(x) dH_n(x) - \int_0^{H^{-1}(\alpha)} g(x) dH_n(x) \right\} + \\ & \quad \left\{ \int_0^{H^{-1}(\alpha)} g(x) dH_n(x) - \int_0^{H^{-1}(\alpha)} g(x) dH(x) \right\} \end{aligned}$$

$$\equiv \gamma_{n,1} + \gamma_{n,2}, \text{ say.}$$

We first consider the case  $\alpha < 1$ . Now if  $I(A)$  is the indicator of  $A$

$$\gamma_{n,2} = \left\{ n^{-1} \sum_{i=1}^n g(Y_i) I(Y_i < H^{-1}(\alpha)) - \int_0^{H^{-1}(\alpha)} g(x) dH(x) \right\}$$

and thus by the strong law of large numbers (SLLN) we obtain immediately

$$\gamma_{n,2} \xrightarrow{L_1} 0. \text{ It remains to show } \gamma_{n,1} \xrightarrow{L_1} 0.$$

Let  $(\Omega, \mathcal{F}, P)$  be the underlying probability space and  $\epsilon > 0$  be arbitrary.

Define

$$G_n = \{w \in \Omega : |Y_{n,\tau_n}(w) - H^{-1}(\alpha)| > \epsilon\}$$

$$E_{n,1} = \{(x, w) \in \mathbb{R}^+ \times \Omega : Y_{n,\tau_n} > x \geq H^{-1}(\alpha)\}$$

$$E_{n,2} = \{(x, w) \in \mathbb{R}^+ \times \Omega : Y_{n,\tau_n} \leq x < H^{-1}(\alpha)\}$$

Then  $G_n, E_{n,1}, E_{n,2}$  are measurable sets and

$$|\gamma_{n,1}| \leq \int_{E_{n,1} \cup E_{n,2}} |g(x)| |I(x < Y_{n,\tau_n}) - I(x < H^{-1}(\alpha))| dH_n(x)$$

for each  $w \in \Omega$ . But

$$E(|\gamma_{n,1}| I_{G_n}) \leq E\left(\int_0^\infty |g(x)| I_{G_n} dH_n(x)\right) \leq E(I_{G_n} n^{-1} \sum_{i=1}^n |g(Y_i)|).$$

Since  $n^{-1}v_n \rightarrow \alpha$  in probability and  $H$  is continuous it follows that  $E(I_{G_n}) = P(G_n) \rightarrow 0$  and since  $n^{-1} \sum_{i=1}^n |g(Y_i)| \rightarrow_{L_1} E|g(Y_1)|$  by the SLLN we get

$$E(|\gamma_{n,1}| I_{G_n}) \rightarrow 0. \quad (4.3)$$

Now

$$|\gamma_{n,1}| I_{\bar{G}_n} \leq \sum_{i=1}^n \int_{E_{n,i}} |g(x)| I_{\bar{G}_n} dH_n(x) \equiv \gamma_{n,3} + \gamma_{n,4}, \text{ say, where } \bar{G}_n \text{ is the}$$

complement of  $G_n$  in  $\Omega$ .

For  $(x, w) \in E_{n,1}$ ,  $w \in \bar{G}_n$  we have  $H^{-1}(\alpha) \leq x < Y_{n,\tau_n} \leq H^{-1}(\alpha) + \epsilon$  and for  $(x, w) \in E_{n,2}$ ,  $w \in \bar{G}_n$ ,  $H^{-1}(\alpha) > x \geq Y_{n,\tau_n} > H^{-1}(\alpha) - \epsilon$ . Therefore

$$\gamma_{n,3} \leq \int_{H^{-1}(\alpha)}^{H^{-1}(\alpha)+\epsilon} |g(x)| dH_n(x) \rightarrow_{L_1} \int_{H^{-1}(\alpha)}^{H^{-1}(\alpha)+\epsilon} |g(x)| dH(x)$$

$$\text{and similarly } \gamma_{n,4} \leq \int_{H^{-1}(\alpha)-\epsilon}^{H^{-1}(\alpha)} |g(x)| dH_n(x) \rightarrow_{L_1} \int_{H^{-1}(\alpha)-\epsilon}^{H^{-1}(\alpha)} |g(x)| dH(x).$$

Since  $E|g(Y)| < \infty$  and  $\epsilon > 0$  is arbitrary we have shown  $E(|\gamma_{n,1}| I_{\bar{G}_n}) \rightarrow 0$

and so  $\gamma_{n,1} \rightarrow_{L_1} 0$ . This establishes the lemma for the case  $\alpha < 1$ .

For  $\alpha = 1$  we interpret  $H^{-1}(\alpha) = +\infty$  and so must show

$$n^{-1} \sum_{i=1}^n g(Y_{n,i}) \rightarrow_{L_1} \int_0^\infty g(x) dH(x) = Eg(Y).$$



We proceed as in (4.2). The proof of  $\gamma_{n,2} \rightarrow_{L_1} 0$  is essentially the same and for  $\gamma_{n,1}$  we write

$$\gamma_{n,1} = \int_0^\infty g(x) \{I_{E_n} - 1\} dH_n(x)$$

where  $E_n = \{(x, w) \in \mathbb{R}^+ \times \Omega : Y_{n, \tau_n}(w) > x\}$ . Also define

$K_n = \{w \in \Omega : |n^{-1} \tau_n(w) - 1| > \epsilon\}$ . Then as before  $\gamma_{n,1} I_{K_n} \rightarrow_{L_1} 0$ . For

$(x, w) \in E_n$ ,  $w \in \bar{K}_n$  we have  $x \geq Y_{n, [n(1-\epsilon)]}$ . So

$$\begin{aligned} |\gamma_{n,1}| I_{\bar{K}_n} &\leq \int_0^\infty |g(x)| I(x \geq Y_{n, [n(1-\epsilon)]}) dH_n(x) \\ &\leq \int_0^\infty |g(x)| dH_n(x) - n^{-1} \sum_{i=1}^{[n(1-\epsilon)]} |g(Y_{n,i})|. \end{aligned} \quad (4.4)$$

Therefore from the first part and the SLLN the right hand side of (4.4) converges in  $L_1$  to  $\int_0^\infty |g(x)| dH(x) - \int_0^{H^{-1}(1-\epsilon)} |g(x)| dH(x)$ , which can be made arbitrarily small by choosing  $\epsilon$  appropriately. This completes the proof.

The next result is based on a theorem by Sen (1961). We assume that  $H$  admits a density (with respect to Lebesgue measure  $\mu$ )  $h$  on  $\mathbb{R}^+$  and  $h(0) > 0$ .

Lemma 4.2. Let  $g : \mathbb{R}^+ \rightarrow \mathbb{R}$  be right continuous in a neighborhood of the origin and have a right derivative  $g'(0)$  there. Suppose  $E|g(Y)|^a < \infty$  for some  $a > 0$ . Then

$$\lim_{n \rightarrow \infty} E\{n^a |g(Y_{n,1}) - g(0)|^a\} = \Gamma(a+1) \{|g'(0)|/h(0)\}^a.$$

Proof.  $E\{n^a |g(Y_{n,1}) - g(0)|^a\} = n^{a+1} \int_0^{x_{n,0}} |g(x) - g(0)|^a (1-H(x))^{n-1} dH(x)$

$$+ n^{a+1} \int_{x_{n,0}}^\infty |g(x) - g(0)|^a (1-H(x))^{n-1} dH(x)$$

$$\equiv \delta_{n,1} + \delta_{n,2}, \text{ say.}$$



The point  $x_{n,0} \in (0, \infty)$  is chosen such that  $H(x_{n,0}) = cn^{-\delta}$  where  $c > 0$  and  $0 < \delta < 1$ . Now  $(1 - H(x))$  is nonincreasing and so

$$\begin{aligned} \delta_{n,2} &\leq n^{a+1} (1 - H(x_{n,0}))^{n-1} \int_{x_{n,0}}^{\infty} |g(x) - g(0)|^a dH(x) \\ &\leq n^{a+1} (1 - H(x_{n,0}))^{n-1} E|g(Y_1) - g(0)|^a \end{aligned}$$

But  $n^{a+1} (1 - H(x_{n,0}))^n \leq n^{a+1} \exp(-cn^{1-\delta}) \rightarrow 0$  as  $n \rightarrow \infty$ . So  $\delta_{n,2} \rightarrow 0$  and

we are left with  $\delta_{n,1}$ . Now  $\delta_{n,1} = n^{a+1} \int_0^{cn^{-\delta}} |g(H^{-1}(x)) - g(0)|^a (1-x)^{n-1} dx$ .

We can find  $c_n \in (0, cn^{-\delta}]$  such that for sufficiently large  $n$

$$\delta_{n,1} = \{|g(H^{-1}(c_n)) - g(0)|/c_n\}^a n^{a+1} \int_0^{cn^{-\delta}} x^a (1-x)^{n-1} dx.$$

It is shown in Sen (1961) that  $n^{a+1} \int_0^{cn^{-\delta}} x^a (1-x)^{n-1} dx \rightarrow \Gamma(a+1)$  as  $n \rightarrow \infty$ . Also

$$\begin{aligned} \lim_{n \rightarrow \infty} \{|g(H^{-1}(c_n)) - g(0)|/c_n\} &= \lim_{n \rightarrow \infty} \{|g(H^{-1}(c_n)) - g(0)|/H^{-1}(c_n)\} \\ &\quad \cdot \lim_{n \rightarrow \infty} \{H^{-1}(c_n)/c_n\} = |g'(0)|/h(0), \end{aligned}$$

and thus the conclusion of the lemma follows.

The following lemma is central to the development of our main theorems.

Lemma 4.3. Suppose assumptions (A1) - (A3) hold. Then

for any sequence of stopping variables  $v_n$  adapted to  $\{\mathcal{B}_{n,k} : 1 \leq k \leq n\}$  for  
which  $n^{-1}v_n \rightarrow \alpha \in (0,1]$  in  $P_{\theta_0}$ -probability,

$$n^{-1}v_{n,v_n} \xrightarrow{L_1} J_{\alpha}.$$

Proof. In the sequel we suppress  $\theta_0$  throughout. From (2.4) and (2.13)

we have  $v_{n,v_n} = \sum_{i=1}^{v_n} \sigma_{n,i}^{*2}$  where for each  $1 \leq i \leq n$ ,

$$\sigma_{n,i}^{*2} = \dot{r}^2(Z_{i-1}) + \beta_0 + \beta_1 + \beta_2 + \beta_3 \quad (4.5)$$

and

$$\beta_0 \equiv E ((\dot{r}^2(Z_i) - \dot{r}^2(Z_{i-1})) | \mathcal{B}_{n,i-1})$$

$$\beta_1 \equiv E ((n - i + 1)^2 (\dot{G}(Z_i) - \dot{G}(Z_{i-1}))^2 | \mathcal{B}_{n,i-1})$$

$$\beta_2 \equiv 2E ((n - i + 1)(\dot{r}(Z_i)\dot{G}(Z_i) - \dot{r}(Z_{i-1})\dot{G}(Z_{i-1})) | \mathcal{B}_{n,i-1})$$

$$\beta_3 \equiv -2\dot{G}(Z_{i-1})E ((n - i + 1)(\dot{r}(Z_i) - \dot{r}(Z_{i-1})) | \mathcal{B}_{n,i-1}).$$

Now (A1) and (A2) ensure the continuity of  $\dot{G}$  and  $\dot{r}$  and the existence of their derivatives at  $Z_{i-1}$ . Also  $\frac{\partial}{\partial x} \dot{G}(x) = -r(x)\dot{r}(x)$ . Furthermore if for each  $n \geq i \geq 1$ ,  $Y_1, \dots, Y_{n-i+1}$  are iidrv's with df given by  $\tilde{F}(x) = (F(x) - F(Z_{i-1})) / (1 - F(Z_{i-1}))$ , if  $x > Z_{i-1}$  and zero otherwise, then the conditional distribution of  $Z_i$  given  $\mathcal{B}_{n,i-1}$  is the same as that of  $\min\{Y_1, \dots, Y_{n-i+1}\}$ . Hence applying Lemma 4.2 repeatedly we find that for each  $n \geq i \geq 1$   $\beta_0, \beta_1, \beta_2, \beta_3$  are respectively convergent equivalent a.s. ( $P_{\theta_0}$ ) to 0,  $2\dot{r}^2(Z_{i-1})$ ,  $-2\dot{r}^2(Z_{i-1}) + 2\{r^{-1}(x)\dot{G}(x) \frac{\partial}{\partial x} \dot{r}(x)\}_{x=Z_{i-1}}$  and  $-2\{r^{-1}(x)\dot{G}(x) \frac{\partial}{\partial x} \dot{r}(x)\}_{x=Z_{i-1}}$ . Hence  $\sum_{j=0}^3 \beta_j$  is convergent equivalent a.s. to 0 and we get  $n^{-1}V_{n,v_n}$  convergent equivalent a.s. to  $n^{-1} \sum_{i=1}^n \dot{r}^2(Z_{i-1})$ . An application of Lemma 4.1 yields the desired result.

We shall now turn to the analysis of the statistics  $\Lambda_{n,\tau_n}(u)$  with  $u$  fixed. In the sequel  $\theta_0$  will be held fixed and therefore we suppress  $\theta_0$  in  $P_{\theta_0}$  and  $E_{\theta_0}$ . This convention will also apply to the ancillary entities to be introduced below. Convergences are to be interpreted with respect to  $P_{\theta_0}$ .

Define  $\{\eta_{n,i} : 1 \leq i \leq n\}$  by

$$\eta_{n,i} \equiv \eta_{n,i}(u) = (g_{n,i}(\theta_n) / g_{n,i}(\theta_0))^{1/2} - 1, \quad (4.6)$$

where  $g_{n,i}(\theta) \equiv g_{n,i}(Z_i, \theta) = q_{\theta}^{1/2}(Z_i | B_{n,i-1})$  and  $\theta_n$  is given by (2.5). Denote differentiation with respect to  $\theta$  by a prime. If  $\|\cdot\|$  denotes the  $L_2$ -norm with respect to the product of Lebesgue measure  $\mu$  and counting measure on  $\{1, \dots, \tau_n(w)\}$  then

$$\begin{aligned} \|g'_{n,i}(\theta) - g'_{n,i}(\theta_0)\|^2 &= \sum_{i=1}^{\tau_n} \int_{Z_{i-1}}^{\infty} (g'_{n,i}(z, \theta) - g'_{n,i}(z, \theta_0))^2 d\mu(z) \\ &\leq \sup_{|\theta - \theta_0| \leq |u|n^{-1/2}} \sum_{i=1}^n \int_{Z_{i-1}}^{\infty} (g'_{n,i}(z, \theta) - g'_{n,i}(z, \theta_0))^2 d\mu(z), \end{aligned}$$

for each  $u$  and hence (A6) entails

$$\lim_{n \rightarrow \infty} E\{n^{-1} \sup_{|\theta - \theta_0| \leq |u|n^{-1/2}} \|g'_{n,i}(\theta) - g'_{n,i}(\theta_0)\|^2\} = 0. \quad (4.7)$$

We shall utilize the following lemma in the proof of Theorem 3.1.

Lemma 4.4. For each  $u \in R$

$$E\left(\sum_{i=1}^{\tau_n} \left(\eta_{n,i}(u) - \frac{1}{2} u n^{-1/2} \xi_{n,i}^*\right)^2\right) \rightarrow 0 \quad (4.8)$$

and

$$E\left(\sum_{i=1}^{\tau_n} \eta_{n,i}^2(u)\right) \rightarrow \frac{1}{4} u^2 J_{\alpha}. \quad (4.9)$$

Proof: Since  $\tau_n$  is adapted to  $\{B_{n,i} : 1 \leq i \leq n\}$  the expectation in (4.8) may be written

$$E\left(\sum_{i=1}^{\tau_n} E\left\{\left(\eta_{n,i} - \frac{1}{2} u n^{-1/2} \xi_{n,i}^*\right)^2 \middle| B_{n,i-1}\right\}\right) \quad (4.10)$$

and the sum of the conditional expectations in (4.10) can be re-expressed as  $\|(\eta_{n,i} - \frac{1}{2} u n^{-1/2} \xi_{n,i}^*)g_{n,i}\|^2$ . Hence to prove (4.8) we must show

$$E\left(\|(\eta_{n,i} - \frac{1}{2} u n^{-1/2} \xi_{n,i}^*)g_{n,i}\|^2\right) \rightarrow 0. \quad (4.11)$$

Observe that for each  $i$ ,  $1 \leq i \leq n$

$$(g_{n,i}(\theta_n) - g_{n,i}(\theta_0)) - u n^{-1/2} g'_{n,i} = \int_{\theta_0}^{\theta_n} (g'_{n,i}(\theta) - g'_{n,i}(\theta_0)) d\mu(\theta). \quad (4.12)$$

But  $g'_{n,i}/g_{n,i} = \frac{1}{2} \xi_{n,i}^*$  and thus (4.12) leads to

$$\|(\eta_{n,i} - \frac{1}{2} u n^{-1/2} \xi_{n,i}^*) g_{n,i}\|^2 = \sum_{i=1}^{\tau_n} \int_{Z_{i-1}}^{\infty} \left( \int_{\theta_0}^{\theta_n} (g'_{n,i}(\theta) - g'_{n,i}(\theta_0)) d\mu(\theta) \right) d\mu(z). \quad (4.13)$$

An application of the Cauchy-Schwarz inequality and Fubini's theorem in turn on the right hand side of (4.13) will yield after some routine manipulations

$$\|(\eta_{n,i} - \frac{1}{2} u n^{-1/2} \xi_{n,i}^*) g_{n,i}\|^2 \leq u^2 n^{-1} \sup_{|\theta - \theta_0| \leq |u| n^{-1/2}} \|g'_{n,i}(\theta) - g'_{n,i}(\theta_0)\|^2 \quad (4.14)$$

and so (4.11) is a consequence of (4.7) and (4.14). Observe that in our notation

$$\|\eta_{n,i} g_{n,i}\|^2 = \sum_{i=1}^{\tau_n} E(\eta_{n,i}^2 | \mathcal{B}_{n,i-1}) \quad (4.15)$$

and

$$\|\frac{1}{2} u n^{-1/2} \xi_{n,i}^* g_{n,i}\|^2 = \frac{1}{4} u^2 n^{-1} \sum_{i=1}^{\tau_n} E(\xi_{n,i}^{*2} | \mathcal{B}_{n,i-1}) = \frac{1}{4} u^2 n^{-1} v_{n,\tau_n}. \quad (4.16)$$

By Lemma 4.3  $n^{-1} v_{n,\tau_n} \rightarrow J_\alpha$  in  $L_1(P)$ . Therefore from (4.15), (4.16) and the inequality

$$\|\eta_{n,i} g_{n,i}\| - \|\frac{1}{2} u n^{-1/2} \xi_{n,i}^* g_{n,i}\| \leq \|(\eta_{n,i} - \frac{1}{2} u n^{-1/2} \xi_{n,i}^*) g_{n,i}\|^2$$

(4.9) follows from (4.8). The proof of the lemma is now complete.

Proof of Theorem 3.1. From our definition of  $\Lambda_{n,\tau_n}$  and  $\eta_{n,i}$  we can write by Taylor's theorem

$$\log \Lambda_{n,\tau_n} = 2 \sum_{i=1}^{\tau_n} \log(1 + \eta_{n,i}) = 2 \sum_{i=1}^{\tau_n} \eta_{n,i} - \sum_{i=1}^{\tau_n} \eta_{n,i}^2 + \sum_{i=1}^{\tau_n} \lambda_{n,i} |\eta_{n,i}|^3, \quad (4.17)$$



where  $\lambda_{n,i}$  satisfy  $|\lambda_{n,i}| < 1$  and  $\max_{1 \leq i \leq \tau_n} |\eta_{n,i}| < \varepsilon$ , with  $\varepsilon > 0$  arbitrary. We rewrite (4.17) in the form

$$\log \Lambda_{n,\tau_n} = \gamma_{n,1} + \gamma_{n,2} + \gamma_{n,3} + \gamma_{n,4} \quad (4.18)$$

where

$$\gamma_{n,1} = 2 \left\{ \sum_{i=1}^{\tau_n} \eta_{n,i} - \frac{1}{2} u n^{-1/2} \sum_{i=1}^{\tau_n} \xi_{n,i}^* + \frac{1}{8} u^2 J_\alpha \right\}, \quad (4.19)$$

$$\gamma_{n,2} = - \left\{ \sum_{i=1}^{\tau_n} \eta_{n,i}^2 - \frac{1}{4} u^2 J_\alpha \right\}, \quad (4.20)$$

$$\gamma_{n,3} = \sum_{i=1}^{\tau_n} \lambda_{n,i} |\eta_{n,i}|^3, \quad (4.21)$$

$$\gamma_{n,4} = \{ u n^{-1/2} J_{n,\tau_n} W_{n,\tau_n} - \frac{1}{2} u^2 J_\alpha \}. \quad (4.22)$$

Hence from Lemma 4.3, (3.2) will be established once we show  $\gamma_{n,i} \xrightarrow{P} 0$  for  $i = 1, 2, 3$  and  $L(W_{n,\tau_n} | P_{\theta_0}) \rightarrow N(0,1)$ . We begin with the proof of the latter.

In view of (A3) and (A5) we have  $E(\xi_{n,i}^* | \mathcal{B}_{n,i-1}) = 0$  for each  $i$  and so with  $\xi_{n,k}$  given by (2.9),  $\{\xi_{n,k}, \mathcal{B}_{n,k} : 1 \leq k \leq n\}$  is a zero-mean martingale under  $P$ . From Lemma 4.3 and (A4)

$$J_{n,\tau_n}^{-1} \sum_{i=1}^{\tau_n} E(\xi_{n,i}^{*2} | \mathcal{B}_{n,i-1}) = (n^{-1} J_{n,\tau_n})^{-1} (n^{-1} V_{n,\tau_n}) \xrightarrow{P} 1 \quad (4.23)$$

Hence by Durrett and Resnick (1978) Theorem 2.3, we will have  $W_{n,\tau_n} \xrightarrow{L} N(0,1)$  once we establish

$$J_{n,\tau_n}^{-1} \sum_{i=1}^{\tau_n} E(\xi_{n,i}^{*2} I(|\xi_{n,i}^*| > \varepsilon J_{n,\tau_n}^{1/2}) | \mathcal{B}_{n,i-1}) \xrightarrow{P} 0 \quad (4.24)$$

for arbitrary  $\varepsilon > 0$ . Now the entity in (4.24) is dominated by

$$(n^{-1} J_{n,\tau_n})^{-(1+\delta/2)} \{ n^{-1} \sum_{i=1}^{\tau_n} E(|\xi_{n,i}^*|^{2+\delta} | \mathcal{B}_{n,i-1}) \} (n\varepsilon)^{-\delta}, \quad (4.25)$$



where the  $\delta$  comes from (A3). Therefore in view of (A4) and Lemma 4.3, (4.24) will be established once we show

$$\overline{\lim}_{n \rightarrow \infty} n^{-1} E \left( \sum_{i=1}^{\tau_n} |\xi_{n,i}^*|^{2+\delta} \right) < \infty \quad (4.26)$$

With our definition of  $\xi_{n,i}^*$  in (2.12) we have

$$|\xi_{n,i}^*|^{2+\delta} \leq 2^{1+\delta} \{ |\dot{r}(Z_i)|^{2+\delta} + |(n-i+1)(\dot{G}(Z_i) - \dot{G}(Z_{i-1}))|^{2+\delta} \} \quad (4.27)$$

Now summoning Lemma 4.2 and following the argument in Lemma 4.3 we note that for  $n \geq i \geq 1$

$$E \{ |(n-i+1)(\dot{G}(Z_i) - \dot{G}(Z_{i-1}))|^{2+\delta} | \mathcal{B}_{n,i-1} \}$$

is convergent equivalent a.s. to  $\Gamma(3+\delta) |\dot{r}(Z_{i-1})|^{2+\delta}$ . Therefore for arbitrary  $\epsilon > 0$

$$\begin{aligned} n^{-1} E \left( \sum_{i=1}^{\tau_n} |(n-i+1)(\dot{G}(Z_i) - \dot{G}(Z_{i-1}))|^{2+\delta} \right) \\ \leq n^{-1} E \left( \sum_{i=1}^{\tau_n} \{ \Gamma(3+\delta) |\dot{r}(Z_{i-1})|^{2+\delta} \} + \epsilon n \right) \\ \leq \Gamma(3+\delta) E |\dot{r}(X)|^{2+\delta} + \epsilon, \end{aligned} \quad (4.28)$$

and thus from (4.27), (4.28) and (A3), (4.26) entails.

We now consider  $\gamma_{n,2}$  and  $\gamma_{n,3}$ . That  $\gamma_{n,i} \xrightarrow{P} 0$  for  $i = 2, 3$  will follow from

$$\max_{1 \leq i \leq \tau_n} |\eta_{n,i}| \xrightarrow{P} 0 \quad (4.29)$$

and

$$\sum_{i=1}^{\tau_n} \eta_{n,i}^2 \xrightarrow{P} \frac{1}{4} u^2 J_\alpha \quad (4.30)$$

To show this let  $\epsilon > 0$  and  $\eta > 0$  be arbitrary. From Durrett and Resnick (1978) we have the inequality

$$P(\max_{1 \leq i \leq \tau_n} |\eta_{n,i}| > \varepsilon) < \eta + P(\sum_{i=1}^{\tau_n} P(|\eta_{n,i}| > \varepsilon | \mathcal{B}_{n,i-1}) > \eta). \quad (4.31)$$

$$\begin{aligned} \text{But } P(|\eta_{n,i}| > \varepsilon | \mathcal{B}_{n,i-1}) &\leq P(|\eta_{n,i} - \frac{1}{2} u n^{-\frac{1}{2}} \xi_{n,i}^*| > \varepsilon/2 | \mathcal{B}_{n,i-1}) \\ &\quad + P(|\xi_{n,i}^*| > |u|^{-1} \varepsilon n^{-\frac{1}{2}} | \mathcal{B}_{n,i-1}) \\ &\leq 4\varepsilon^{-2} E((\eta_{n,i} - \frac{1}{2} u n^{-\frac{1}{2}} \xi_{n,i}^*)^2 | \mathcal{B}_{n,i-1}) \\ &\quad + u^2 \varepsilon^{-2} n^{-1} E(\xi_{n,i}^{*2} I(|\xi_{n,i}^*| > |u|^{-1} \varepsilon n^{-\frac{1}{2}}) | \mathcal{B}_{n,i-1}) \end{aligned} \quad (4.32)$$

Now (4.24) holds. So from Lemma 4.3 we get

$$n^{-1} \sum_{i=1}^{\tau_n} E(\xi_{n,i}^{*2} I(|\xi_{n,i}^*| > |u|^{-1} \varepsilon n^{-\frac{1}{2}}) | \mathcal{B}_{n,i-1}) \xrightarrow{P} 0. \quad (4.33)$$

Furthermore from (4.8)  $\sum_{i=1}^{\tau_n} E((\eta_{n,i} - \frac{1}{2} u n^{-\frac{1}{2}} \xi_{n,i}^*)^2 | \mathcal{B}_{n,i-1}) \xrightarrow{P} 0$  and therefore (4.29) obtains. Again with  $\varepsilon, \eta > 0$  arbitrary,

$$\begin{aligned} P(|\sum_{i=1}^{\tau_n} \eta_{n,i}^2 - \frac{1}{4} u^2 n^{-1} \sum_{i=1}^{\tau_n} \xi_{n,i}^{*2}| > \varepsilon) &\leq \varepsilon^{-1} E(|\sum_{i=1}^{\tau_n} \eta_{n,i}^2 - \frac{1}{4} u^2 n^{-1} \xi_{n,i}^{*2}|) \\ &\leq \frac{1}{2} \varepsilon^{-1} \eta E(\sum_{i=1}^{\tau_n} (\eta_{n,i} - \frac{1}{2} u n^{-\frac{1}{2}} \xi_{n,i}^*)^2) + \varepsilon^{-1} n^{-1} (E(\sum_{i=1}^{\tau_n} \eta_{n,i}^2 + \frac{1}{4} u^2 n^{-1} J_{n,\tau_n})). \end{aligned} \quad (4.34)$$

Select  $\eta = \{E(\sum_{i=1}^{\tau_n} (\eta_{n,i} - \frac{1}{2} u n^{-\frac{1}{2}} \xi_{n,i}^*)^2)\}^{-\frac{1}{2}}$  and apply Lemma 4.3 and 4.4.

We get from (4.34)

$$(\sum_{i=1}^{\tau_n} \eta_{n,i}^2 - \frac{1}{4} u^2 n^{-1} \sum_{i=1}^{\tau_n} \xi_{n,i}^{*2}) \xrightarrow{P} 0, \quad (4.35)$$

and then using McLeish (1974) (Theorem 3.6 and Corollary 3.8) we get

$$n^{-1} \sum_{i=1}^{\tau_n} \xi_{n,i}^{*2} \xrightarrow{P} J_\alpha \quad \text{and then (4.30) follows from (4.35).}$$

It remains to show  $\gamma_{n,1} \xrightarrow{P} 0$ . Note that (4.34) and (4.35) also imply

$$\sum_{i=1}^{\tau_n} E(\eta_{n,i}^2 | \mathcal{B}_{n,i-1}) \xrightarrow{P} \frac{1}{4} u^2 J_\alpha \quad (4.36)$$

and therefore directly from (4.6)

$$\sum_{i=1}^{\tau_n} E(\eta_{n,i} | \mathcal{B}_{n,i-1}) \stackrel{P}{\rightarrow} -\frac{1}{8} u^2 J_\alpha. \quad (4.37)$$

For arbitrary  $\varepsilon > 0$

$$\begin{aligned} P\left(\left|\sum_{i=1}^{\tau_n} \eta_{n,i} - \frac{1}{2} u n^{-1/2} \sum_{i=1}^{\tau_n} \xi_{n,i}^* + \frac{1}{8} u^2 J_\alpha\right| > \varepsilon\right) \\ \leq P\left(\left|\sum_{i=1}^n \zeta_{n,i}\right| > \varepsilon/2\right) + P\left(\left|\sum_{i=1}^{\tau_n} E(\eta_{n,i} | \mathcal{B}_{n,i-1}) + \frac{1}{8} u^2 J_\alpha\right| > \varepsilon/2\right) \end{aligned} \quad (4.38)$$

where  $\zeta_{n,i} = \eta_{n,i} - \frac{1}{2} u n^{-1/2} \xi_{n,i}^* - E(\eta_{n,i} | \mathcal{B}_{n,i-1})$ ,  $1 \leq i \leq n$ .

Now  $\{\zeta_{n,i}, \mathcal{B}_{n,i}; 1 \leq i \leq n\}$  is a zero-mean martingale. So we have

$$P\left(\left|\sum_{i=1}^{\tau_n} \zeta_{n,i}\right| > \varepsilon/2\right) \leq 4\varepsilon^{-2} E\left(\sum_{i=1}^{\tau_n} \zeta_{n,i}^2\right) \quad (4.39)$$

and

$$\begin{aligned} E\left(\sum_{i=1}^{\tau_n} \zeta_{n,i}^2\right) &\leq E\left(\sum_{i=1}^{\tau_n} \zeta_{n,i}^2\right) \\ &= E\left(\sum_{i=1}^{\tau_n} E(\zeta_{n,i}^2 | \mathcal{B}_{n,i-1})\right) \\ &\leq E\left(\sum_{i=1}^{\tau_n} \left(\eta_{n,i} - \frac{1}{2} u n^{-1/2} \xi_{n,i}^*\right)^2\right) \end{aligned} \quad (4.40)$$

That  $\gamma_{n,1} \xrightarrow{P} 0$  now follows from (4.38), (4.39), (4.40) and (4.8). The proof of Theorem 3.1 is now complete.

Proof of Theorem 3.2. Observe that (3.3) is an immediate consequence of Theorem 3.1. We also note that this entails

$$L(\log \Lambda_{n, \tau_n}(u) | P_{n, \theta_0}) \rightarrow N(-\frac{1}{2} \sigma^2, \sigma^2) \quad (4.41)$$

where  $\sigma^2 = u^2 J_\alpha$  and  $P_{n, \theta_0}$  as before is the restriction of  $P_{\theta_0}$  to  $\mathcal{B}_{n, \tau_n}$ . Hence by LeCam's First Lemma (see Hájek and Sidak (1967)) it follows that the family of probability measures  $\{P_{n, \theta_n} : n \geq 1\}$  is contiguous to  $\{P_{n, \theta_0} : n \geq 1\}$  and so we have for each  $u \in \mathbb{R}$

$$L(\log \Lambda_{n, \tau_n}(u) | P_{n, \theta_n}) \rightarrow N(\frac{1}{2}\sigma^2, \sigma^2) \quad (4.42)$$

from which (3.4) follows.

Proof of Theorem 3.3. Since

$$\lambda_n(\theta) = \sum_{k=1}^n \int_{E_{n,k}} T_{n,k}(z^{(k)}) p_{\theta}(z^{(k)}, n) d\mu_k(z^{(k)}),$$

we obtain

$$\begin{aligned} \frac{d}{d\theta} \lambda_n(\theta) &= \sum_{k=1}^n \int_{E_{n,k}} T_{n,k}(z^{(k)}) \xi_{n,k}(z^{(k)}, \theta) p_{\theta}(z^{(k)}, n) d\mu_k(z^{(k)}) \quad (4.43) \\ &= E_{\theta}(T_{n, \tau_n} \xi_{n, \tau_n}). \end{aligned}$$

We have already noted that our assumptions imply  $E_{\theta}(\xi_{n, \tau_n}) = 0$ . Thus (4.43) can be rewritten

$$E_{\theta}(\xi_{n, \tau_n} (T_{n, \tau_n} - \lambda_n(\theta))) = \frac{d}{d\theta} \lambda_n(\theta) \equiv \lambda'_n(\theta) \quad (4.44)$$

and an application of the Cauchy-Schwarz inequality yields (3.5). When equality obtains in (3.5) there is a constant  $a_n(\theta)$  such that

$$T_{n, \tau_n} - \lambda_n(\theta) = a_n(\theta) \xi_{n, \tau_n}. \quad (4.45)$$

Hence  $a_n^2(\theta) = (\lambda'_n(\theta))^2 / J_{n, \tau_n}(\theta)$ . From Lemma 4.3 and the fact that

$L(W_{n, \tau_n} | P_{\theta_0}) \rightarrow N(0, 1)$  the conclusion of the theorem follows from (4.45).

Proof of Theorem 3.4. Suppose the sequence  $\{T_{n, \tau_n}\}$  satisfies the condition

$$L[n^{1/2}(T_{n, \tau_n} - \theta_0) | P_{\theta_0}] \rightarrow N(0, v_{\alpha}^2(\theta_0)), \quad (4.46)$$

where  $v_{\alpha}^2(\theta_0) > 0$ , and in addition the restriction

$$\liminf_{n \rightarrow \infty} P_{\theta_0 + n^{-1/2}}[T_{n, \tau_n} < \theta_0 + n^{-1/2}] \leq \frac{1}{2}. \quad (4.47)$$



We shall show  $v_{\theta}^2(\theta_0) \geq J_{\alpha}^{-1}(\theta_0)$ .

Let  $\varepsilon > 0$  be arbitrary. Set  $\theta_n = \theta_0 + n^{-1/2}$  and define the sets  $C_n = [\lambda_{n,\tau_n} > \varepsilon]$ ,  $D_n = [T_{n,\tau_n} \geq \theta_n]$ ,  $n \geq 1$  where  $\lambda_{n,\tau_n} = \log \Lambda_{n,\tau_n}(1)$ . Then in view of (4.47),

$$\limsup_{n \rightarrow \infty} P_{\theta_n}(D_n) \geq 1/2. \quad (4.48)$$

Also

$$P_{\theta_n}(C_n) = 1 - P_{\theta_n}[(\lambda_{n,\tau_n} - 1/2\sigma^2)/\sigma \leq (\varepsilon - 1/2\sigma^2)/\sigma]$$

where  $\sigma^2 = J_{\alpha}(\theta_0)$ . Hence from Theorem 3.2 we get

$$\lim_{n \rightarrow \infty} P_{\theta_n}(C_n) = 1 - \Phi((\varepsilon - 1/2\sigma^2)/\sigma) \quad (4.49)$$

where  $\Phi$  is the standard Gaussian distribution function. Hence selecting  $\varepsilon > 1/2\sigma^2$ , (4.48) and (4.49) lead to the inequalities

$$\limsup_{n \rightarrow \infty} P_{\theta_n}(D_n) \geq 1/2 > \lim_{n \rightarrow \infty} P_{\theta_n}(C_n). \quad (4.50)$$

Thus for infinitely many  $n$ ,

$$P_{\theta_n}(D_n) > P_{\theta_n}(C_n). \quad (4.51)$$

By the Neyman-Pearson Lemma the test based on  $\lambda_{n,\tau_n}$  is the most powerful test of its size among all tests whose stopping variable is  $\tau_n$ . So we have from (4.51)

$$P_{\theta_0}(D_n) > P_{\theta_0}(C_n) \quad (4.52)$$

for infinitely many  $n$ . But

$$P_{\theta_0}(D_n) = 1 - P_{\theta_0}[n^{1/2}(T_{n,\tau_n} - \theta_0)/v_{\alpha}(\theta_0) < v_{\alpha}^{-1}(\theta_0)]$$

and



$$P_{\theta_0}(C_n) = 1 - P_{\theta_0}[(\lambda_{n,\tau_n} + \frac{1}{2}\sigma^2)/\sigma \leq (\varepsilon + \frac{1}{2}\sigma^2)/\sigma].$$

Hence (4.51) implies  $\Phi((\varepsilon + \frac{1}{2}\sigma^2)/\sigma) \geq \Phi(v_\alpha^{-1}(\theta_0))$ , in view of (4.46) and Theorem 3.2. Since  $\varepsilon > \frac{1}{2}\sigma^2$  but is otherwise arbitrary we get the result  $v_\alpha^2(\theta_0) \geq \sigma^{-2} = J_\alpha^{-1}(\theta_0)$ .

Now suppose (4.46) holds with  $\theta_0$  replaced by  $\theta$ , for any  $\theta \in \Theta$ . The function given by  $g_n(\theta) = |P_\theta[T_{n,\tau_n} < \theta] - \frac{1}{2}|$ ,  $\theta \in \Theta$  and zero otherwise, is Borel-measurable (with respect to the Borel subsets of  $\Theta$ ) and our assumption implies  $\lim_{n \rightarrow \infty} P_\theta(T_{n,\tau_n} < \theta) = \frac{1}{2}$ , for all  $\theta \in \Theta$ . Hence

$$\lim_{n \rightarrow \infty} g_n(\theta) = 0 \quad \text{and} \quad 0 \leq g_n(\theta) \leq \frac{1}{2}, \quad \text{for each } \theta \in \Theta.$$

Therefore since

$$\int_R g_n(\theta + n^{-\frac{1}{2}}) d\Phi(\theta) = \int_R g_n(\theta) \frac{1}{\sqrt{2\pi}} \exp(-\frac{1}{2}(\theta - n^{-\frac{1}{2}})^2) d\mu(\theta),$$

the dominated convergence theorem yields

$$\lim_{n \rightarrow \infty} \int_R g_n(\theta + n^{-\frac{1}{2}}) d\Phi(\theta) = 0.$$

It follows that  $g_{n_v}(\theta + n_v^{-\frac{1}{2}}) \rightarrow 0$  a.e.  $(\Phi)$  along some subsequence  $(n_v)$ .

But the measure in  $(R, \mathcal{B})$  induced by  $\Phi$  is equivalent to Lebesgue measure  $\mu$ .

So for almost all  $\theta \in \Theta$  (respect to  $\mu$ ) we have  $\liminf_{n \rightarrow \infty} g_n(\theta + n^{-\frac{1}{2}}) = 0$

and thus also  $\liminf_{n \rightarrow \infty} P_{\theta + n^{-\frac{1}{2}}}[T_{n,\tau_n} < \theta + n^{-\frac{1}{2}}] \leq \frac{1}{2}$ , for almost all  $\theta \in \Theta$ ,

and so the conclusion  $v_\alpha^2(\theta) \geq J_\alpha^{-1}(\theta)$  can be made for almost all  $\theta \in \Theta$ .

The stated form of Theorem 3.4 will now follow with only minor modifications.

### 5. Concluding Remarks.

The restriction to nonnegative random variables made at the beginning of this paper is unnecessary and our results will continue to hold with minor modifications in more general cases. With the appropriate changes for instance our results will hold true for distributions having a finite right end-point.

The particular choice of local coordinates  $\theta_n = \theta + un^{-1/2}$  of (2.5) in the definition of the PCLRS  $\{\Lambda_{n,k}\}$  in (2.6) was a consequence of the convergence  $n^{-1}J_{n,\tau_n} \rightarrow J_\alpha$  deduced from Lemma 4.3 and (A4). It was at this stage where the consideration of the observables  $\{Z_i\}$  as order statistics came into play.

The proof of the main result Theorem 3.1 reveals two basic features. Firstly we derive the limiting normal distribution for the sequence of derivatives of the log-likelihood  $\{\xi_{n,k}(\theta_0) : 1 \leq k \leq n\}$  and then analyze terms of a particular Taylor expansion of the log-likelihood ratios  $\{p_{\theta_n}(Z^{(k)}, n)/p_{\theta_0}(Z^{(k)}, n) : 1 \leq k \leq n\}$ . In this expansion the weak continuity condition (A6) makes third order terms negligible in probability. The basic tools utilized in the derivation of the limiting distribution of  $W_{n,\tau_n}$  of (2.14) were the martingale character of  $\{\xi_{n,k}(\theta_0), B_{n,k} : 1 \leq k \leq n\}$  which is a consequence of (A5), the existence of the limit for stopped suitably normalized conditional variances  $V_{n,\tau_n}$ , as proved in Lemma 4.3 and the (conditional) Lindeberg condition (4.24) which we derived using (A3).

With these remarks in mind we outline below a set of conditions under which the local asymptotic normality can be obtained for likelihood ratio statistics where the underlying observations follow a series scheme.

Suppose  $\{X_{n,k} : 1 \leq k \leq n; n \geq 1\}$  is a double sequence of random variables on a probability space  $(X, \mathcal{A}, P_\theta)$  where  $\theta \in \mathcal{C}$  and  $\mathcal{C}$  is an open

subset of  $R$ . Let  $\tilde{X}_{n,k} = (X_{n,1}, \dots, X_{n,k})$ ,  $1 \leq k \leq n$  and  $\mathcal{B}_{n,k}$  denote the  $\sigma$ -field generated by  $\tilde{X}_{n,k}$ . The projection of  $P_\theta$  to  $\mathcal{B}_{n,k}$  is denoted  $P_{n,\theta}^{(k)}$  and we suppose there is some  $\sigma$ -finite measure  $\mu$  on  $(X, A)$  such that  $P_{n,\theta}^{(k)}$  is absolutely continuous with respect to the product  $\mu_k = \mu \times \mu \times \dots \times \mu$  on the cartesian product  $(X^k, A^k)$ . As before, for each  $n \geq 1$  let  $\tau_n$  be a stopping variable adapted to  $\{\mathcal{B}_{n,k} : 1 \leq k \leq n\}$  and let  $P_{n,\theta}$  denote the restriction of  $P_\theta$  to  $\mathcal{B}_{n,\tau_n} = \sigma(\tilde{X}_{n,\tau_n})$ .

If  $p_\theta(\tilde{x}_{n,k}; n)$  is the pdf of  $\tilde{X}_{n,k}$  and  $q_\theta(x_{n,k} | \mathcal{B}_{n,k-1})$  the conditional pdf of  $X_{n,k}$  given  $\mathcal{B}_{n,k-1}$  we have

$$P_\theta(\tilde{X}_{n,k}; n) = \prod_{i=1}^k q_\theta(X_{n,i} | \mathcal{B}_{n,i-1}), \quad 1 \leq k \leq n. \quad (5.1)$$

Let  $\theta_0$  be a fixed point in  $\Theta$ . We assume

(B1) For all  $\theta$  in some neighborhood  $N_{\theta_0}$  of  $\theta_0$  and all  $\tilde{x}_{n,k}$ ,  $p_\theta(\tilde{x}_{n,k}; n) > 0$ ,  $1 \leq k \leq n$ ;  $\theta \rightarrow p_\theta(\tilde{x}_{n,k}; n)$  is continuously differentiable on  $N_{\theta_0}$  for  $\mu_k$ -almost all  $\tilde{x}_{n,k}$ .

(B2) For each  $n \geq 1$  and all  $k$ ,  $\theta \rightarrow \int_X q_\theta(x | \mathcal{B}_{n,k-1}) d\mu$  is differentiable under the integral sign at  $\theta_0$ .

We may now define for  $1 \leq k \leq n$ ,

$$\xi_{n,k} = \left[ \frac{\partial}{\partial \theta} \log p_\theta(\tilde{X}_{n,k}; n) \right]_{\theta=\theta_0} \quad (5.2)$$

$$\xi_{n,k}^* = \left[ \frac{\partial}{\partial \theta} \log q_\theta(X_{n,k} | \mathcal{B}_{n,k-1}) \right]_{\theta=\theta_0}. \quad (5.3)$$

We also assume

(B3) For each  $n \geq 1$  and all  $k$ ,  $0 < E_{\theta_0}(\xi_{n,k}^{*2}) < \infty$ . Let us then define

$$V_{n,k} = \sum_{i=1}^k E_{\theta_0}(\xi_{n,i}^{*2} | \mathcal{B}_{n,i-1}), \quad 1 \leq k \leq n \quad (5.4)$$

and suppose

(B4) There exists a sequence of positive constants  $\{\psi_n : n \geq 1\}$  such that  $V_{n,\tau_n}/\psi_n \rightarrow 1$  in  $P_{\theta_0}$ -probability.

(B5) For all  $\varepsilon > 0$

$$\psi_n^{-1} \sum_{i=1}^{\tau_n} E_{\theta_0} (\xi_{n,i}^{*2} I(|\xi_{n,i}^*| > \varepsilon \psi_n^{1/2}) | \mathcal{B}_{n,i-1}) \rightarrow 0$$

in  $P_{\theta_0}$ -probability.

(B6) For each  $u \in R$

$$\lim_{n \rightarrow \infty} E_{\theta_0} \left\{ \sup_{|\theta - \theta_0| \leq |u| \psi_n^{-1/2}} \psi_n^{-1} \sum_{i=1}^{\tau_n} \int_X d\mu \left[ \frac{\partial}{\partial \theta} \{q_{\theta}(x | \mathcal{B}_{n,i-1})\}^{1/2} - \frac{\partial}{\partial \theta_0} \{q_{\theta_0}(x | \mathcal{B}_{n,i-1})\}^{1/2} \right]^2 \right\} = 0$$

$$\text{where } \frac{\partial}{\partial \theta} \{q_{\theta}(x | \mathcal{B}_{n,i-1})\}^{1/2} = \left( \frac{\partial}{\partial \theta} \{q_{\theta}(x | \mathcal{B}_{n,i-1})\}^{1/2} \right)_{\theta = \theta_0}.$$

In view of our assumptions we now define

$$\Lambda_{n,k}(u) = p_{\theta_n}(X_{n,k}; n) / p_{\theta_0}(X_{n,k}; n), \quad 1 \leq k \leq n \quad (5.5)$$

where  $\theta_n = \theta_0 + u \psi_n^{-1/2} \in \Theta$ ,  $u \in R$  and set

$$\Lambda_{n,\tau_n}(u) = \Lambda_{n,k}(u), \quad \text{if } \tau_n = k \quad (5.6)$$

Hence paralleling Theorem 3.1 we state

Theorem 5.1. With the definitions (5.2)-(5.6) and under conditions

B1-B6, for each  $u \in R$

$$\Lambda_{n,\tau_n}(u) = \exp\{u \Delta_n - \frac{1}{2} u^2 + \delta_n\}$$

where  $\Delta_n = \xi_{n,\tau_n} / \psi_n^{1/2}$  and  $L(\Delta_n | P_{\theta_0}) \rightarrow N(0,1)$  and  $\delta_n(u) \rightarrow 0$  in  $P_{\theta_0}$ -probability for each  $u \in R$ . We may therefore say the family of probability measures  $\{P_{n,\theta} : \theta \in \Theta\}$  is LAN at  $\theta_0$ .



### Acknowledgements

A preliminary version of the results in this paper appeared in the author's Ph.D. dissertation prepared at the University of North Carolina, Chapel Hill. The author wishes to express his thanks to Professor P.K. Sen for his comments and guidance in this research.

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REPORT DOCUMENTATION PAGE		READ INSTRUCTIONS BEFORE COMPLETING FORM
1. REPORT NUMBER	2. GOVT ACCESSION NO.	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) Local Asymptotic Normality for Progressively Censored Likelihood Ratio Statistics and Applications		5. TYPE OF REPORT & PERIOD COVERED
		6. PERFORMING ORG. REPORT NUMBER RM-394
7. AUTHOR(s) Joseph C. Gardiner		8. CONTRACT OR GRANT NUMBER(s) N00014-79-C0522
9. PERFORMING ORGANIZATION NAME AND ADDRESS Department of Statistics & Probability Michigan State University East Lansing, Michigan 48824		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS
11. CONTROLLING OFFICE NAME AND ADDRESS ONR-Statistics & Probability Program (Code 436) Arlington, VA 22217		12. REPORT DATE November 1979
		13. NUMBER OF PAGES 26
14. MONITORING AGENCY NAME & ADDRESS (if different from Controlling Office)		15. SECURITY CLASS. (of this report) UNCLASSIFIED
		15a. DECLASSIFICATION/DOWNGRADING SCHEDULE
16. DISTRIBUTION STATEMENT (of this Report)  APPROVED FOR PUBLIC RELEASE: DISTRIBUTION UNLIMITED.		
17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)		
18. SUPPLEMENTARY NOTES		
19. KEY WORDS (Continue on reverse side if necessary and identify by block number) Clinical trials, life-testing, likelihood ratio statistics, progressive censoring, stopping variables.		
20. ABSTRACT (Continue on reverse side if necessary and identify by block number) Let $X_{n,1} \leq X_{n,2} \leq \dots \leq X_{n,n}$ be the ordered variables corresponding to a random sample of size $n$ with respect to a family of probability measures $\{P_\theta: \theta \in \Theta\}$ where $\Theta$ is an open subset of the real line. In many practical situations the $X_{n,i}$ are the observables and experimentation must be curtailed prior to $X_{n,n}$ . If $\tau_n$ is a stopping variable adapted		

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20.

to the  $\sigma$ -fields  $\{\sigma(X_{n,1}, \dots, X_{n,k}) : 1 \leq k \leq n\}$  and  $P_{n,\theta}$  the projection of  $P_\theta$  onto  $\sigma(X_{n,1}, \dots, X_{n,\tau_n})$ , the local asymptotic normality of the stopped progressively censored likelihood ratio statistics

$\Lambda_{n,\tau_n} = dP_{n,\theta_n} / dP_{n,\theta}$  is established with  $\theta, \theta_n = \theta + un^{-1/2} \in \Theta$  and  $\theta, u$  held fixed, under certain conditions on the underlying distribution and on  $\tau_n$ . Conditions are also given to ensure the local asymptotic normality of likelihood ratio statistics where the underlying observations are given in a series scheme.

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